Journal of Hydrology 574 (2019) 169–180

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Research papers

A new station-enabled multi-sensor integrated index for drought monitoring

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ARTICLE INFO

This manuscript was handled by Huaming Guo, Editor-in-Chief, with the assistance of Di Long, Associate Editor

Keywords:
Climate change
CONUS
Drought monitoring
GIIDI_station
GWR
PCA

ABSTRACT

Remote sensing data are frequently incorporated into drought indices used widely by research and management communities to assess and diagnose current and historic drought events. The integrated drought indices combine multiple indicators and reflect drought conditions from a range of perspectives (i.e., hydrological, agricultural, meteorological). However, the success of most remote sensing based drought indices is constrained by geographic regions since their performance strongly depends on environmental factors such as land cover type, temperature, and soil moisture. To address this limitation, we propose a framework for a new integrated drought index that performs well across diverse climate regions. Our framework uses a geographically weighted regression model and principal component analysis to composite a range of vegetation and meteorological indices derived from multiple remote sensing platforms and *in-situ* drought indices developed from meteorological station data. Our new index, which we call the station-enabled Geographically Independent Integrated Drought Index (GIIDI_station), compared favorably with other common drought indices such as Microwave Integrated Drought Index (MIDI), Optimized Meteorological Drought Index (OMDI), Precipitation Condition Index (PCI), Temperature Condition Index (TCI), Soil Moisture Condition Index (SMCI), and Vegetation Condition Index (VCI). Using Pearson correlation analyses between remote sensing and *in-situ* drought indices during the growing season (April to October) from 2002 to 2011, we show that GIIDI_station had the best correlations with *in-situ* drought indices. Across the entire study region of the continental United States, the performance of GIIDI_station was not affected by common environmental factors such as precipitation, temperature, land cover and soil conditions. Taken together, our results suggest that GIIDI_station has considerable potential to improve our ability of monitoring drought at regional scales, provided local meteorological station data are available.

1. Introduction

There is an increasing need for comprehensive and reliable drought monitoring to aid planning and mitigation of drought impacts, since the frequency and consequences of droughts are expected to intensify under climate change (Halwatura et al., 2017; Keyantash and Dracup, 2004; Wilhelmi and Wilhite, 2002; Zhou et al., 2012). Historically, droughts have been classified and assessed using point observations from networks of meteorological stations. For instance, the widely-used Standardized Precipitation Index (SPI), which is the World Meteorological Organization's (WMO) recommended indicator for meteorological drought, is based on ground-based precipitation observations (Hayes et al., 1999; McKee et al., 1993). More recently, global and near-real-time observations of remote sensing technology open the door for comprehensively characterizing drought conditions regionally and globally, especially in regions with limited sampling gauges (Jiao et al., 2019; Lu et al., 2016; Rhee et al., 2010; Wang et al., 2012; Wu et al., 2013; Zhang et al., 2017). Various drought indices building on remote sensing observations have been developed to estimate drought conditions. Table 1 provides a summary of the commonly used drought

Abbreviations: AMSR-E, Advanced Microwave Scanning Radiometer for EOS; GIIDI_station, station-enabled Geographically Independent Integrated Drought Index; GWR, Geographically Weighted Regression; LST, Land Surface Temperature; LULC, land use/land cover; MIDI, Microwave Integrated Drought Index; MODIS, Moderate Resolution Imaging Spectroradiometer; MPDI, Modified Perpendicular Drought Index; NLCD, National Land Cover Data; OMDI, Optimized Meteorological Drought Index; PCA, Principal Component Analysis; PCI, Precipitation Condition Index; PDI, Perpendicular Drought Index; PDSI, Palmer Drought Severity Index; SDCI, Scaled Drought Condition Index; SDI, Synthesized Drought Index; SMCI, Soil Moisture Condition Index; SPI, Standardized Precipitation Index; TCI, Temperature Condition Index; TVDI, Temperature Vegetation Dryness Index; USDM, United States Drought Monitor; VCI, Vegetation Condition Index; VegDRI, Vegetation Drought Response Index; VIUPD, Vegetation Index based on the Universal Pattern Decomposition method

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https://doi.org/10.1016/j.jhydrol.2019.04.037
Received 2 October 2018; Received in revised form 12 April 2019; Accepted 13 April 2019
Available online 15 April 2019
0022-1694/

Table 1
Description of commonly used drought indices. The data source column indicates the satellite name, meteorological observation data or single drought indices used for the integrated drought indices (MIDI and OMDI). The method column shows the main method for establishing drought indices.

Drought index	Data source	Method	Source
PDSI	Precipitation, temperature, and soil moisture	Based on water balance model	(Palmer, 1965)
SPI	Precipitation	Based on the historical precipitation occurrence probability distribution function	(McKee et al., 1993)
Z-index	PDSI	Based on PDSI anomaly	(Palmer, 1965)
SPEI	Potential evapotranspiration and precipitation	Based on the historical deficiency of precipitation (P-PET) occurrence probability distribution function	(Vicente-Serrano et al., 2010)
USDM	SPI, PDSI, soil moisture, NDVI and other indicators	Local expert knowledge	(Svoboda et al., 2002)
RDI	Precipitation and evapotranspiration	Similar to SPEI but using $\frac{P}{ET}$	(Mu et al., 2013)
VegDRI	NDVI, Phenology and other indicators	Classification and regression tree (CART)	(Brown et al., 2008)
SWI	Precipitation and ET_o	Based on residual water-energy ratio and probability-based function	(Liu et al., 2017)
VCI	MODIS NDVI	$(NDVI_{ikj}\text{-}NDVI_{i,min})/(NDVI_{i,max}\text{-}NDVI_{i,min})$	(Kogan, 1995)
TCI	MODIS LST	$(LST_{i,max}\text{-}LST_{ijk})/(LST_{i,max}\text{-}LST_{i,min})$	(Kogan, 1997)
SMCI	AMSR-E Soil moisture	$(SM_{ikj}\text{-}SM_{i,min})/(SM_{i,max}\text{-}SM_{i,min})$	(Rhee et al., 2010)
PCI	TRMM precipitation	$(TRMM_{ikj}\text{-}TRMM_{i,min})/(TRMM_{i,max} + TRMM_{i,min})$	(Zhang and Jia, 2013)
MIDI	TCI, SMCI, PCI	Empirical weights	(Zhang and Jia, 2013)
OMDI	TCI, SMCI, PCI	Constrained optimization	(Hao et al., 2015)

*LST_{ijk}, SM_{ijk}, $TRMM_{ijk}$—monthly LST, SM, TRMM for pixel i, in month j, for year k, respectively. $LST_{i,min}$, $SM_{i,min}$, $TRMM_{i,min}$—multi-year minimum LST, SM, TRMM, respectively, for pixel i. $LST_{i,max}$, $SM_{i,max}$, $TRMM_{i,max}$—multi-year maximum LST, SM, TRMM, respectively.

indices.

However, many of the existing remote-sensing drought indices are linked to a single biophysical variable (e.g., precipitation, soil moisture, greenness), and may not be sufficient to capture the complex processes and diverse impacts of drought (AghaKouchak et al., 2015; Hao and Singh, 2015). There is an urgent need to develop integrated indices which could combine station data and remote sensing observations to alleviate the shortcomings of drought characterization from a single index. Several studies have focused on developing integrated remote-sensing drought indices to provide a more robust and comprehensive estimation of drought. For example, the Microwave Integrated Drought Index (MIDI) (Zhang and Jia, 2013), Scaled Drought Condition Index (SDCI) (Rhee et al., 2010), Optimized Meteorological Drought Index (OMDI) and Optimized Vegetation Drought Index (OVDI) (Hao et al., 2015), Synthesized Drought Index (SDI) (Du et al., 2013) combined variables from multiple perspectives (e.g., Soil Moisture Condition Index (SMCI), Precipitation Condition Index (PCI), Temperature Condition Index (TCI) and Vegetation Condition Index (VCI)). These indices have been shown to perform well in selected study areas (Du et al., 2013; Hao et al., 2015; Rhee et al., 2010; Zhang and Jia, 2013).

A major challenge for these integrated, remote-sensing indices is their relatively poor performance when applied to climate regions different from those in which they were developed since they were optimized under a narrow range of environmental conditions. Another major issue is their inability to adequately represent spatial variability, due to their reliance on traditional composition methods (Park et al., 2016). Specifically, it is often assumed that all areas within a study region contribute the same weight for a particular single index. This type of integration is straightforward to implement and is commonly used to develop multivariate drought indices. However, this type of integration is not well suited for capturing the covariability of drought-related indices, since it may miss local details that can be significant if the relationship of the related indices is spatially non-stationary (AghaKouchak et al., 2015). A third limitation is that traditionally integrated drought indices only use a single *in-situ* based drought index as the dependent variable to combine the multi-source remote sensing data. For example, OVDI uses SPI as the dependent variable to determine the weights of PCI, TCI, SMCI and VCI (Hao et al., 2015). Similarly, Vegetation Drought Response Index (VegDRI) only uses Palmer Drought Severity Index (PDSI) as the dependent variable to composite multi-source data (Brown et al., 2008). However, only one dependent variable may not be sufficient to estimate comprehensive drought conditions as they affect hydrological, vegetative, and meteorological conditions. For the regions with both station data and remote sensing images, the integration of ground observation information from multiple perspectives and the remote sensing observations from multi-sensors could be a better way to comprehensively monitor drought.

To address these issues, the objective of this study is to develop and evaluate a new integrated drought index based on multi-sensor remote sensing data for drought monitoring under different climate conditions. In this study, Geographically Weighted Regression (GWR) model and Principal Component Analysis (PCA) were used to composite and integrate multiple remote sensing based drought indices. GWR and PCA were used because they can take the local details into consideration (e.g., using different weights in different parts of the study area for a particular single index), thus the newly developed index can be applied to diverse climate regions. We also used three *in-situ* based drought indices (PDSI, moisture anomaly index (Z-index) and SPI) as dependent variables to composite multi-source single indices. We call the new product the station-enabled Geographically Independent Integrated Drought Index (GIIDI_station) indicating its universal applicability for diverse climate regions. To evaluate the performance of GIIDI_station, it was compared with both integrated drought indices (MIDI, OMDI) and single drought indices (PCI, TCI, VCI, and SMCI). We also evaluated whether environmental factors impact the performance of GIIDI_station across spatial climate gradients.

2. Data

Both *in-situ* and remote sensing datasets were used to develop and assess the performance of our GIIDI_station. These data were also used to compare GIIDI_stations's performance with other remote sensing-based drought indices in various climate divisions over the continental United States (CONUS), focusing on the growing season from 2002 to 2011. The product of Advanced Microwave Scanning Radiometer for EOS (AMSR-E) was used in the development of GIIDI_station and the AMSR-E data was available from 2002 to 2011.

2.1. *In-situ based drought indices*

Three monthly *in-situ* drought indices, PDSI, moisture anomaly index (Z-index), and Standardized Precipitation Index (SPI) were selected for incorporation into GIIDI_station because they are among the most commonly used indicators for drought monitoring in the United States. These *in-situ* drought indices, which provide general assessment of soil moisture and precipitation conditions, were obtained from the

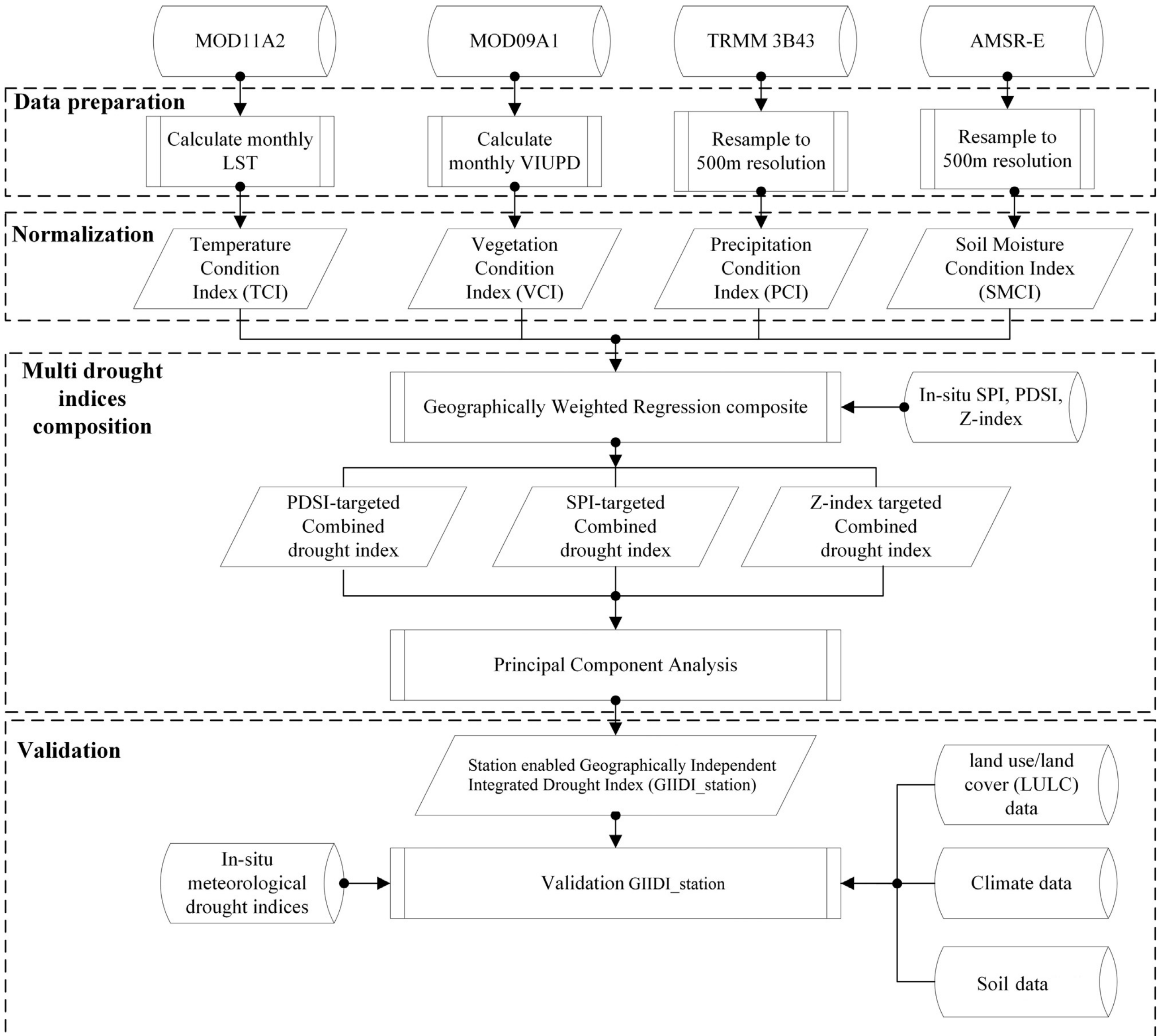

Fig. 1. Flowchart of comprehensive drought estimation based on multi-source remote sensing data.

NOAA's National Climatic Data Center (NCDC–NOAA) repository for 344 climatic divisions in the CONUS (http://www1.ncdc.noaa.gov/pub/data/cirs/). These selected *in-situ* indices also have been widely applied by various studies to evaluate remote sensing drought indices (Brown et al., 2008; Caccamo et al., 2011; Ji and Peters, 2003; Rhee et al., 2010). In our study, the PDSI, Z-index and SPI from 1012 observation stations were used as training data, and climate division level based PDSI, Z-index and SPI were used as evaluation data.

2.2. Remote sensing data

Four remote based drought indices – Moderate Resolution Imaging Spectroradiometer (MODIS) data based VCI and TCI, AMSR-E based SMCI, and TRMM-based PCI – were selected for incorporation into GIIDI_station. These four remote sensing based drought indices estimate drought conditions from unique perspectives. The VCI, which is derived from Vegetation Index based on the Universal Pattern Decomposition method (VIUPD), estimates drought conditions based on vegetative response. It was calculated using MODIS land surface data (MOD09A1) downloaded from the Land Processes Distributed Active Center (LPDAAC; http://lpdaac.usgs.gov/). TCI describes temperature anomaly during the drought events. Monthly TCI was calculated using MODIS Land Surface Temperature (LST) data (MOD11A2), which was obtained from the National Aeronautics and Space Administration's (NASA) earth observing system data and information system (EOSDIS; http://reverb.echo.nasa.gov). PCI provides information on precipitation deficiency. It was calculated based on TRMM 3B43 data, which was available at the NASA Data and Information Services Center (DISC) (http://mirador.gsfc.nasa.gov/). SMCI was selected to describe the soil moisture perspective. We compute SMCI based on the AMSR-E product, obtained from Vrije Universtiteit Amsterdam (http://nsidc.org/).

2.3. Other data

United States Drought Monitor (USDM) data was chosen as a proxy for evaluating the performance of GIIDI_station. USDM combines information from multiple ground-observation based drought indicators and local reports from state climatologists and observers throughout the country, and it is used as a trigger for federal drought relief programs (Brown et al., 2008; Hayes et al., 2012). The USDM map has a spatial resolution at the approximate scale of a climate division (Svoboda et al., 2002). The USDM classifies droughts as D0 (abnormally dry), D1

(moderate drought), D2 (severe drought), D3 (extreme drought), and D4 (exceptional drought) events. Detailed information about USDM is available at http://drought.unl/dm/.

In order to further evaluate the performance of GIIDI_station, nine additional datasets including land use/land cover (LULC) data, climate data, and soil data were selected to explore whether the performance of GIIDI_station for drought monitoring depends on common environmental factors. The U.S. Geological Survey National Land Cover Data (NLCD) (http://landcover.usgs.gov) was used to describe LULC state. Mean annual precipitation and temperature data were selected to describe climate conditions. Data on estimated mean annual precipitation and temperature in each climate division was obtained from the Oregon State University PRISM group (http://prism.oregonstate.edu) and DISC (http://mirador.gsfc.nasa.gov/), respectively. Information on five soil properties, including permeability, water table depth, available water holding capacity, hydrologic groups and soil drainage, were obtained from the Center for Environmental Informatics at Penn State University (http://www.soilinfo.psu.edu/). A more detailed description of these indices is available from Quiring and Ganesh (2010).

3. Methodology

To develop the composite GIIDI_station index, we first calculated VCI using VIUPD instead of the commonly used NDVI, since the former has been shown to better estimate drought conditions (Jiao et al., 2016). Next, we used the GWR model to composite TCI, VCI, PCI and SMCI. We used three different *in-situ* drought indices (SPI, PDSI and Z-index) as the dependent variables to composite the remote sensing based condition indices (TCI, VCI, PCI and SMCI). There are three outcomes of GWR model based composition: SPI-targeted integrated drought index, PDSI-targeted integrated drought index and Z-index targeted integrated drought index. The PCA method was then used to composite these three outcomes of the GWR into GIIDI_station. To validate the product, we first evaluated the correlation between *in-situ* drought indices and GIIDI_station in different climate divisions. Then the LULC data, climate data and soil data were used to explore whether the performance of GIIDI_station for drought estimation was affected by LULC, precipitation, temperature and soil conditions. More details about our methodology are given in Sections 3.1–3.3, and the overall approach is illustrated in Fig. 1.

3.1. Scaled remote sensing indices

Table 1 shows detailed information about the remote sensing based drought indices used in this study. To reiterate, TCI, PCI, VCI and SMCI were used to develop GIIDI_station, while MIDI and OMDI were used to assess its drought monitoring performance. The analysis in this study focused primarily on the months from April to October in order to avoid noise from the snow and ice in the winter.

3.2. GIIDI_station development and evaluation

The development of GIIDI_station incorporated *in-situ* drought indices (SPI, PDSI, and Z-index) from 1012 observation stations. Supplementary material Fig. 1 shows the locations of the observation stations.

GIIDI_station was calculated using GWR model based on the following equations:

$$Y = \beta_0(\mu, v) + \beta_1(\mu, v)TCI + \beta_2(\mu, v)VCI + \beta_3(\mu, v)PCI + \beta_4(\mu, v)SMCI \quad (1)$$

$$Y = \begin{cases} SPI \\ PDSI \\ Z - index \end{cases} \quad (2)$$

where (μ, v) denotes the geographical coordinates of the 1012 observation stations. $\beta_i(\mu, v)$ represents the weighting of single indices (TCI, VCI, PCI and SMCI). Y is the dependent variable which includes the three widely used *in-situ* drought indices: SPI, PDSI and Z-index. In geographically weighted regression, the parameter estimates are made using an approach in which the contribution of a sample to the analysis is weighted based on its spatial proximity to the specific location under consideration. Data from observations close to the location under consideration are weighted more than data from observations further away. The parameters were estimated from

$$\hat{\beta}(\mu, v) = (X^TW(\mu, v)X)^{-1}X^TW(\mu, v)Y \quad (3)$$

where $\hat{\beta}(\mu, v)$ represents an estimate of β, $W(\mu, v)$ is the weighting matrix, which ensures that observations close to the location at which the parameter estimates are to be made have more influence on the analysis than those further away. $W(\mu, v)$ is a matrix of weights relative to the position of (μ,v) in our study area. W(μ,v) is computed from a weighting scheme that is also known as a kernel (Fotheringham et al., 1998). Gaussian-shaped kernel was used in our study:

$$W_i(u, v) = e^{-0.5\left(\frac{d_i(u,v)}{h}\right)^2} \quad (4)$$

where $W_i(u, v)$ is the geographical weight of the *i*th observation relative to the location (u,v), and (u,v) is the coordinate of observation points. $d_i(u, v)$ is the distance between the grid cells and the location (u,v). h is known as the bandwidth. In our study, the bandwidth was determined based on the corrected Akaike Information Criterion (AICc) (Hurvich et al., 1998) which takes the form below:

$$AIC_c = 2n\log_e(\hat{\sigma}) + n\log_e(2\pi) + n\left(\frac{n + tr(\mathbf{S})}{n - 2 - tr(\mathbf{S})}\right) \quad (5)$$

where n is the number of observations in the dataset, $\hat{\sigma}$ is the estimate of the standard deviation of the residuals, and tr(**S**) is the trace of the hat matrix. The optimum of h could be found based on the least AICc. In this study, GWR model was established using arcpy module in Python. Given that there were three different *in-situ* based drought indices (SPI, PDSI and Z-index) as the dependent variables in Eq. (1), there were three outcomes of the GWR model: SPI-targeted integrated drought indices, PDSI-targeted integrated drought indices and Z-index targeted integrated drought indices. In order to better integrate these three GWR model outputs into one variable, the PCA method was used to composite the three different outcomes into GIIDI_station (see Eqs. (6) and (7)). The basic purpose of using PCA is to reduce the dimensionality of a data set from a large set of variables into a small set of variables (Wold et al., 1987). The first principal component (PC1) of the PCA was selected and the values of the PC1 were normalized as the range of −6 to 6 in corresponding to the range of PDSI. Then the normalized PC1 was defined as GIIDI_station since it accounts for as much of the variability of these three GWR outputs, which were based on the dependent variables of SPI, PDSI and Z-index, respectively. The PCA process was finished in environment for visualizing images (IDL/ENVI) software environment. It also should be noted that 1-month SPI was used as the dependent variable to produce SPI-targeted integrated index as an example. Our framework could also include different time-scales of SPI to obtain different time scales of GIIDI_station.

$$\begin{cases} Y_1\text{=SPI-targeted integrated drought index} \\ Y_2\text{=PDSI-targeted integrated drought index} \\ Y_3\text{=Z index-targeted integreated drought index} \end{cases} \quad (6)$$

$$GIIDI\_station = PCA(Y_1, Y_2, Y_3) \quad (7)$$

We adopted a categorical classification of drought severity for GIIDI_station that is based on the classification system for USDM (abnormally dry, moderate drought, severe drought, extreme drought, and exceptional drought). We examined the cumulative frequency distribution of historical GIIDI_station values, and then delineated the

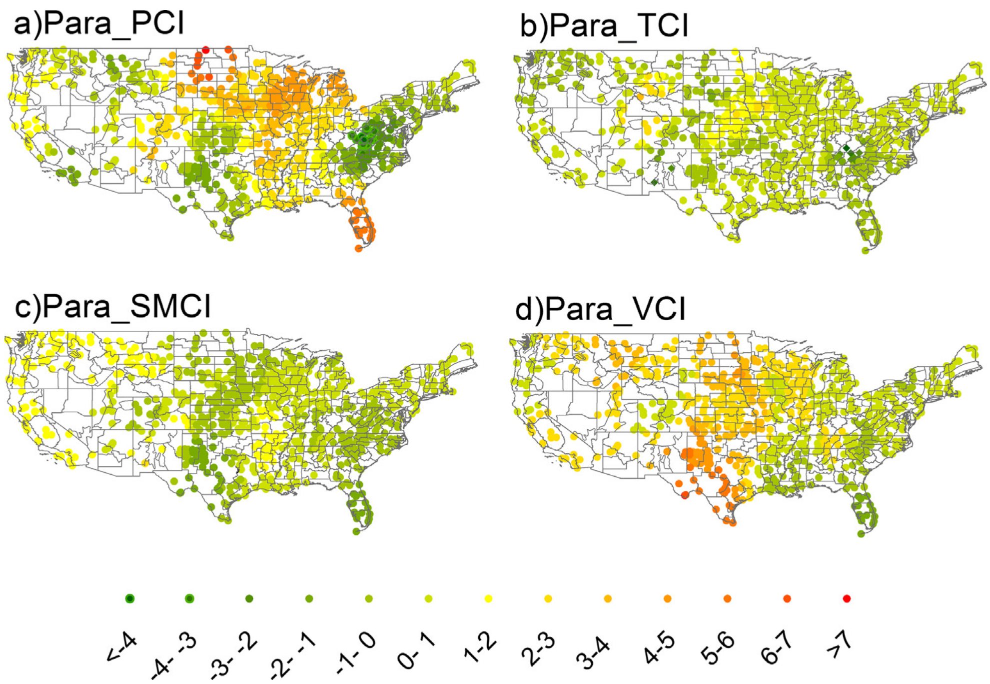

Fig. 2. Spatial distributions of GWR estimated parameters for PDSI simulation in July 2011: (a) parameter for PCI; (b) parameter for TCI; (c) parameter for SMCI; and (d) parameter for VCI.

categories based on the definitions for USDM. The evaluation of GIIDI_station includes three stages. In the first stage, we compared GIIDI_station with PCI, MIDI and OMDI during the growing season (April–October) using the visual comparison method. Here, the years of 2007, 2009 and 2011 were selected as the examples of severe, moderate and extreme drought years, respectively. Pearson correlation between remote sensing drought indices and *in-situ* indices was then used in the second stage to assess the performance of the compared remotely sensed drought indices. In the third stage, nine independent variables were selected in a multivariate regression model to evaluate whether the environmental factors (e.g., LULC, climate and soil variables) could affect the applicability of GIIDI_station.

4. Results

4.1. The significance of GWR and PCA models

Fig. 2 shows an example of the weighting of PCI, TCI, VCI and SMCI, when taking PDSI in July 2011 as the response variable using the GWR model. In Fig. 2, different colors of the points indicate different weighting of each remote sensing based drought index. According to Fig. 2, we can see the weighting of PCI, TCI, VCI and SMCI was spatially heterogeneous. For example, in the southern Great Plains, VCI took higher weighting than other indices, but in the Southeast, the weighting of VCI was lower than other indices. Unlike the spatial homogeneity models, GWR model could provide the criterion weights depend on the spatial variable range of criterion values.

For clarity, in the process of PCA composition, we referred to the integrated drought index developed using PDSI as the dependent variable in GWR as the "PDSI targeted Combined Drought Index (CDI)". Similarly, SPI targeted CDI and Z-index targeted CDI were named when using SPI and Z-index as the dependent variables, respectively. Fig. 3 shows the relationships between GIIDI_station, SPI targeted CDI, PDSI targeted CDI and Z-index targeted CDI for July 2011. According to Fig. 3, there were still differences between SPI-, PDSI- and Z-index targeted CDI, and GIIDI_station achieved better agreement with *in-situ* drought indices after the three CDIs were integrated by PCA. The determination of coefficients (R^2) between PDSI targeted CDI and SPI-, Z-index targeted CDI were 0.318 and 0.259, respectively, while the determination of coefficients (R^2) between GIIDI_station and SPI-, Z-index targeted CDI were 0.737 and 0.612, respectively (Fig. 3). Thus, PCA can effectively combine different information from each *in-situ* drought index based CDI into a newly integrated drought index.

4.2. GIIDI_station drought category definition

To qualitatively classify drought severity, we evaluated the historical and cumulative frequency of county-level GIIDI_station for all the grid cells over the CONUS from the year 2002 to 2011 (Fig. 4). Using drought classification schemes of USDM as a guide, we classified GIIDI_station into six levels based on the historical GIIDI_station frequency distributions. Table 2 shows the range of GIIDI_station for each level. We used −3.5, −2.5, −1.5, −0.5, 0.5 as the thresholds for different categories. The use of these thresholds led to similar cumulative percentiles to USDM. Specifically, the percentile of exceptional drought, extreme drought, severe drought, moderate drought, and abnormally dry for GIIDI_station is 1.8%, 5.6%, 12.4%, 23.8%, and 33.9%, respectively, which is similar to USDM (2% for D4, 5% for D3, 10% for D2, 20% for D1, and 30% for D0).

4.3. Regional drought pattern comparisons

The similarity of the remote sensing drought indices to USDM, and to each other, was assessed by mapping drought conditions over the CONUS during the growing seasons of 2007, 2009, and 2011. As described above, these years were selected to exemplify moderate, slight and severe drought years, respectively. Maps of monthly drought conditions monitored by the USDM, GIIDI_station, OMDI, MIDI and PCI are shown in Figs. 5–7. These figures demonstrate the diversity of information provided by different drought indicators, highlighting the complexity of developing an integrated drought index in various climate regions at the continental scale. Generally, as shown in Figs. 5–7, GIIDI_station shows greater similarity to USDM under all drought conditions when compared to the other drought indices.

In 2011, USDM indicated that the majority of Texas, New Mexico and Georgia experienced extreme drought (D1) beginning in April. The

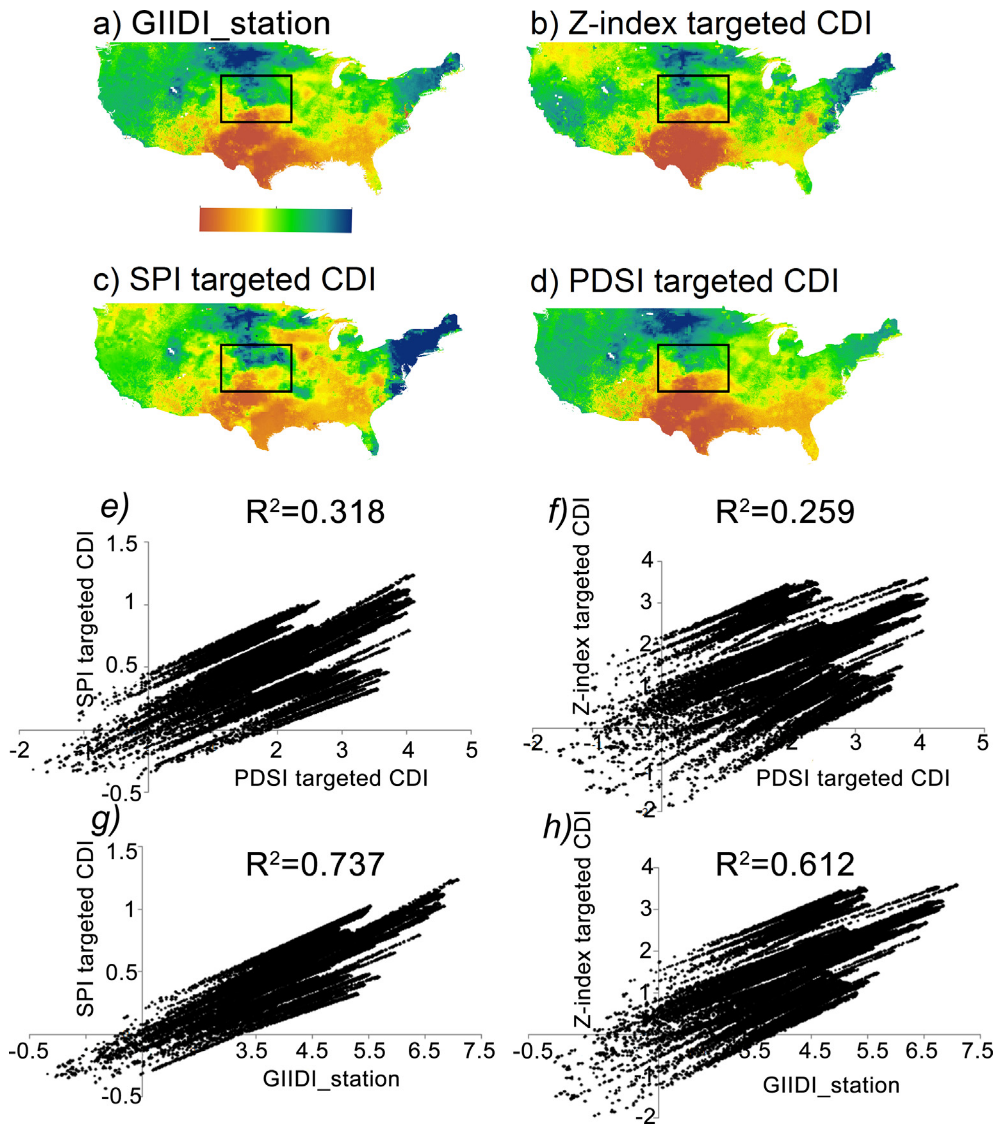

Fig. 3. The correlations between GIIDI_station, SPI-, PDSI- and Z-index targeted CDI. Panel a) stands for the values of GIIDI_station for July 2011; b) to d) represents the values of SPI targeted CDI, PDSI targeted CDI and Z-index targeted CDI for July 2011, respectively. Panel e) – f) show the correlations between GIIDI_station, PDSI-, SPI- and Z-index targeted CDIs for the specified regions using squares in panel a) to d).

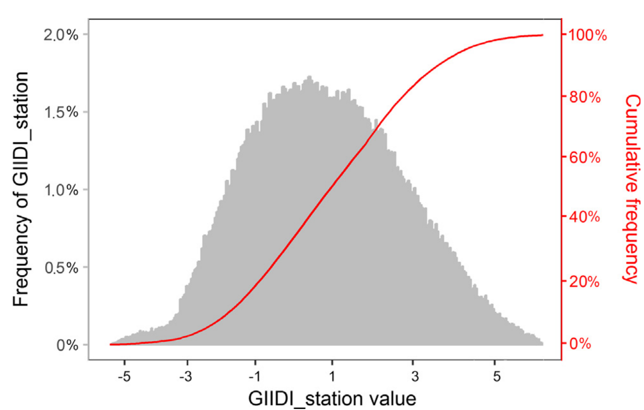

Fig. 4. Frequency and cumulative frequency distribution of GIIDI_station values.

drought then began to expand into northern regions (e.g., Michigan, Iowa and Illinois) and throughout the southeastern by August (see USDM in Fig. 5). All the compared indices indicated a general extreme drought condition from April to May in the south. However, patterns in PCI, OMDI and MIDI were similar but not identical to those in the USDM and GIIDI_station. They showed expansion of the extreme drought areas into the northern Great Plains and northwestern CONUS in June when these regions were identified as drought-free by USDM and GIIDI_station.

Table 2
Drought classification scheme of GIIDI_station.

GIIDI_station Values	Drought Category	Cumulative Percentiles
−0.49 to 0.50	Abnormally Dry	33.9%
−1.49 to −0.50	Moderate Drought	23.8%
−2.49 to −1.5	Severe Drought	12.4%
−3.49 to −2.5	Extreme Drought	5.6%
< −3.5	Exceptional Drought	1.8%
> 0.5	No Drought	66%

Fig. 6 provides additional insights about the performance of the indices during the moderate drought of 2009. The USDM indicated moderate drought in western regions along the coast, and a small region of extreme drought in south Texas. GIIDI_station generally

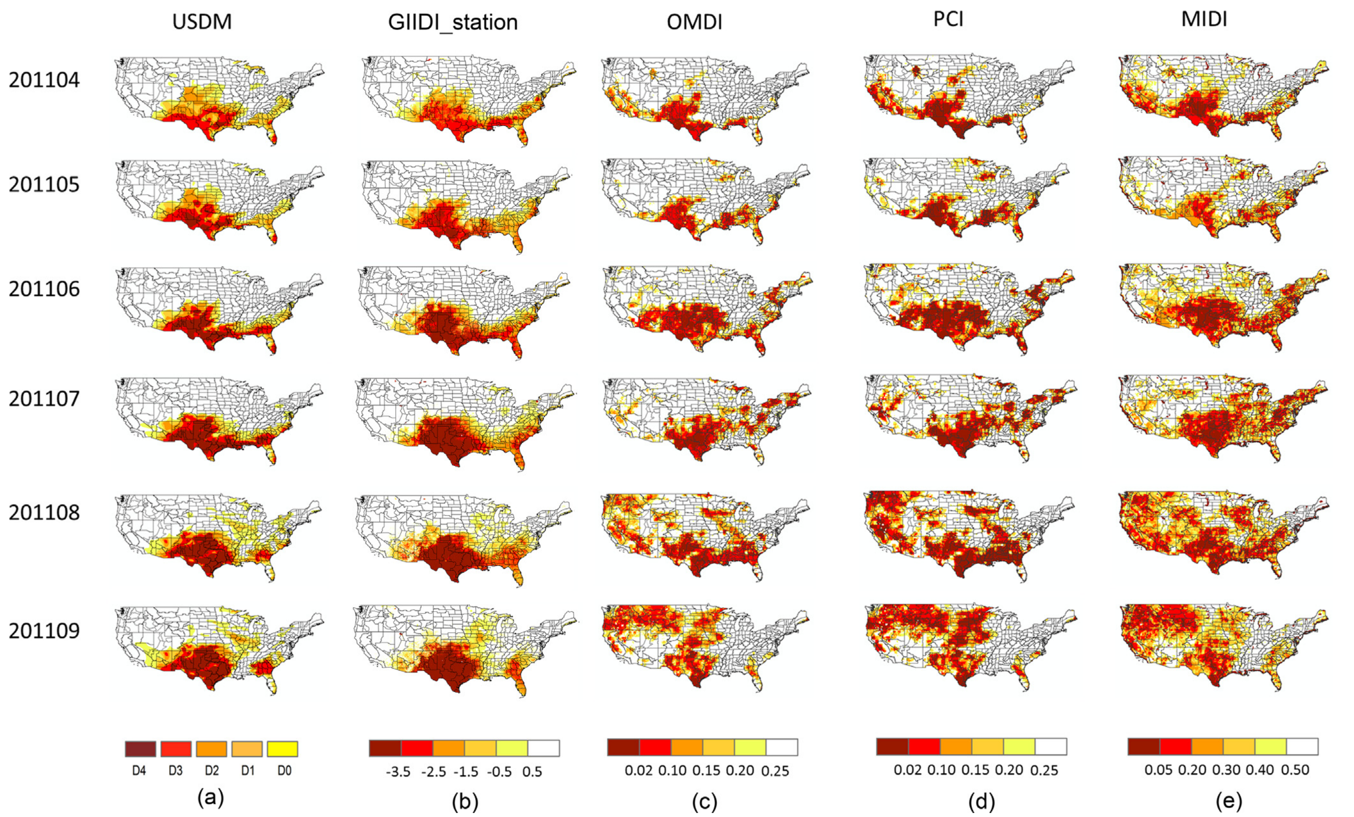

Fig. 5. Drought conditions in the US monitored by multiple drought indices from April to September in 2011. The first column displays the observed USDM drought data for the period of April to October, while the second to fifth columns show the GIIDI_station, OMDI, PCI and MIDI, respectively. For USDM, D0-D4 represents the different severities of drought conditions; for columns 2–5, lower values stand for more severe drought.

captured the drought features in the USDM, while other drought indices showed different patterns. For example, from April to May, PCI, OMDI and MIDI diagnosed drought conditions in the northwestern Great Plains. In September, these indices classified areas of the western and northeastern CONUS as experience severe drought, severe drought in these areas was not identified by USDM and GIIDI_station in 2009.

As shown in Fig. 7, similar results were obtained for the severe drought year of 2007. Based on the USDM data, western regions and areas of the Southeast (Georgia, Alabama, North and South Carolina) experienced D1 (moderate drought) to D2 (severe drought). The drought condition became even more severe (D2 and D3) in southeastern regions by October 2007. PCI, MIDI and OMDI maps showed high inter-index agreement but were less similar to USDM when compared to GIIDI_station. Unlike MIDI, PCI and OMDI, GIIDI_station identified drought conditions in the west and southeastern regions that did not change much in terms of severity from April to October 2007, in reasonable agreement with predictions from the USDM.

4.4. Monthly temporal and spatial correlation comparisons

We compared the correlations between seven remotely sensed drought indices (GIIDI_station, MIDI, OMDI, PCI, TCI, VCI and SMCI) and *in-situ* drought indices (PDSI, Z-Index, 1-, 2-, 3-, 6-, 9-, 12-, and 24-month SPI). Of the remote sensing based indices considered here, GIIDI_station was the most similar to the *in-situ* indices in their temporal ranking of drought conditions (see Tables 3 and 4).

Fig. 8 shows the temporal similarity between the *in-situ* drought indices and each of the remote-sensing drought indices, evaluated as linear correlation within each climate division. GIIDI_station yielded higher performance than the other remote sensing based indices. High correlation values (r-value > 0.6) between GIIDI_station and the *in-situ* drought indices were obtained in almost all the climate divisions, and across the multiple timescales associated with the *in-situ* indices. In the western and northeastern United States, most of the remote sensing based drought indices showed weak correlation (e.g., $r < 0.4$) with *in-situ* drought indices. For example, as shown in Fig. 8, VCI generally correlated significantly only in the southern CONUS. PCI exhibited strong correlations with SPI-1 but not with long-term SPI (SPI-3 and SPI-6) in most of the CONUS.

4.5. Factors influencing the relationships between GIIDI_station and in-situ drought indices

Nine independent variables (LULC, mean annual precipitation, mean annual temperature, permeability, mean soil moisture, organic material in soil, available water holding capacity, hydrologic groups, and soil drainage class) were entered into a stepwise multivariate regression model where the dependent variable was the r-values between GIIDI_station and PDSI, Z-index and SPI. Results showed that there was no significant correlation between the nine independent variables and the performance of GIIDI_station ($p > 0.05$). The stepwise regression model results showed that if four or five variables were included in the regression model, it provided the best regression result (Fig. 9). However, the top four or five significant variables all together explained only 8.3% of the GIIDI_station performance (Fig. 9). This indicates that the performance of GIIDI_station for monitoring drought conditions is not dependent on these nine common environmental factors. In comparison, some previous studies have shown that the performance of other remotely sensed drought indices is strongly dependent on environmental factors (Brown et al., 2008; Ji and Peters, 2003; Quiring and Ganesh, 2010; Zhang et al., 2017). For example, Quiring and Ganesh (2010) demonstrated that the response of VCI to drought conditions is modulated by vegetation type, land use practices and soil type.

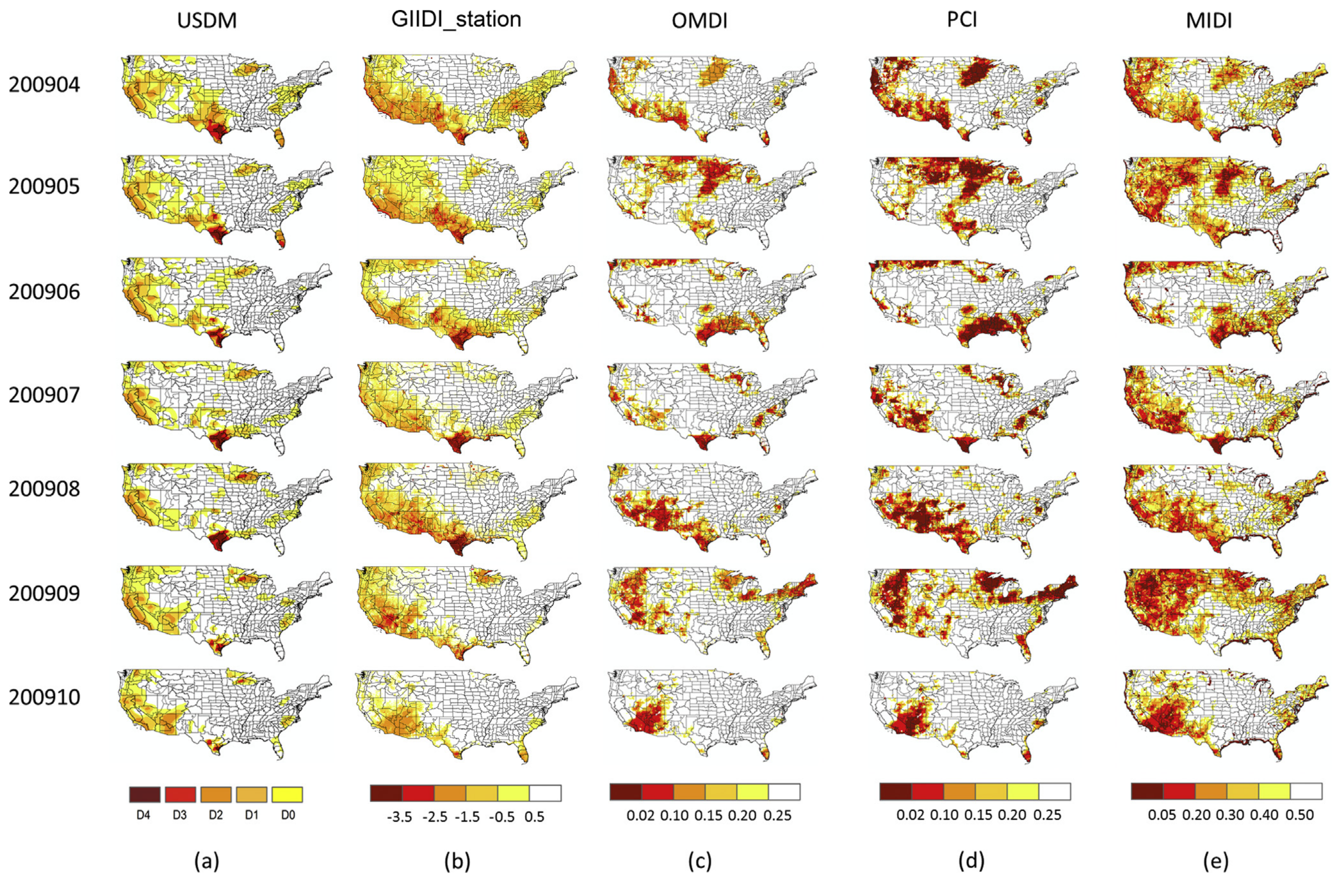

Fig. 6. Drought conditions in the US monitored by multiple drought indices from April to October in 2009. The first column displays the observed USDM drought data for the period of April to October, while the second to fifth columns show the GIIDI_station, OMDI, PCI and MIDI, respectively. For USDM, D0-D4 represents the different severities of drought conditions; for columns 2–5, lower values stand for more severe drought.

5. Discussion

Based on the comparison results, we can draw some general conclusions regarding the applicability of GIIDI_station for drought monitoring across climate divisions. The GIIDI_station provides several unique characteristics for drought monitoring. The most unique characteristics of GIIDI_station for drought monitoring is its potential as a reliable index for drought monitoring across climate regions, linked to the fact that its performance is independent of environmental factors. Previous work indicated that the performances of traditional remote sensing based indices such as VCI depend on precipitation, land cover and other factors (Bayarjargal et al., 2006; Quiring and Ganesh, 2010; Singh et al., 2003; Vicente-Serrano, 2007), and therefore have limited applicability across different regions. For example, for the fifteen remote sensing based drought indices assessed by Zhang et al. (2017), performance of most remote sensing based drought indices is generally good only in Texas and the central CONUS, and is poorer in western and northeastern regions. Compared with these indices, GIIDI_station can perform reasonably well across all different climate regions. Our results indicate that GIIDI_station has high correlation with *in-situ* evaluation drought indices located in almost all the climate regions. In addition, the performance of GIIDI_station for drought monitoring is not influenced by the common environmental factors such as LULC, mean annual precipitation, mean annual temperature, permeability, mean soil moisture, organic material in soil, available water holding capacity, hydrologic groups, and soil drainage class. Another unique characteristic of GIIDI_station for drought monitoring is that it could monitor different severity of drought conditions. We selected 2007, 2009 and 2011 as the severe, moderate and extreme drought examples in our study, and GIIDI_station shows the best match with USDM according to our visual interpretation. In addition, compared with USDM, GIIDI_station does not require knowledge from local experts, which makes the establishment of GIIDI_station much less expensive and time-consuming than USDM.

Several factors could contribute to the superior performance of GIIDI_station for drought monitoring. Firstly, the GWR model, which is used to combine multiple single drought indices and includes the spatial coordinates of the sample sites in the analysis, has the potential to provide a more appropriate basis for the spatial integration of the relationship between variables. Different single indices have different characters and they also have different applicability. Previous studies indicated that VIUPD based VCI performed worse in regions with lower temperature and SMCI performed worse in regions with high density of vegetation cover (Jiao et al., 2016; Zhang et al., 2017), so in relatively cold regions the weighting of VCI should be lower than other indices, and in the high density vegetation covered regions, the weighting of SMCI should be lower. The GWR model is a preferable choice for combining single drought indices because it permits this flexibility in weighting. Because GWR model is a local regression model for spatially varying relationships, it leads to the single indices have their high weights in the regions where they best suitable for. As the parameters from GWR model shown in Fig. 2, high weighting of VCI mainly located on warm regions such as Texas. Similarly, the relatively higher weighting of SMCI mainly located on the sparse vegetation covered region in the West. Our spatial distributions of the weights for the single drought indices are in accordance with the findings of previous studies.

Secondly, the selection of multiple dependent variables is another factor that potentially contributes to the good performance of GIIDI_station. Many previous studies only use one *in-situ* based drought index as the dependent variable to combine multiple dependent

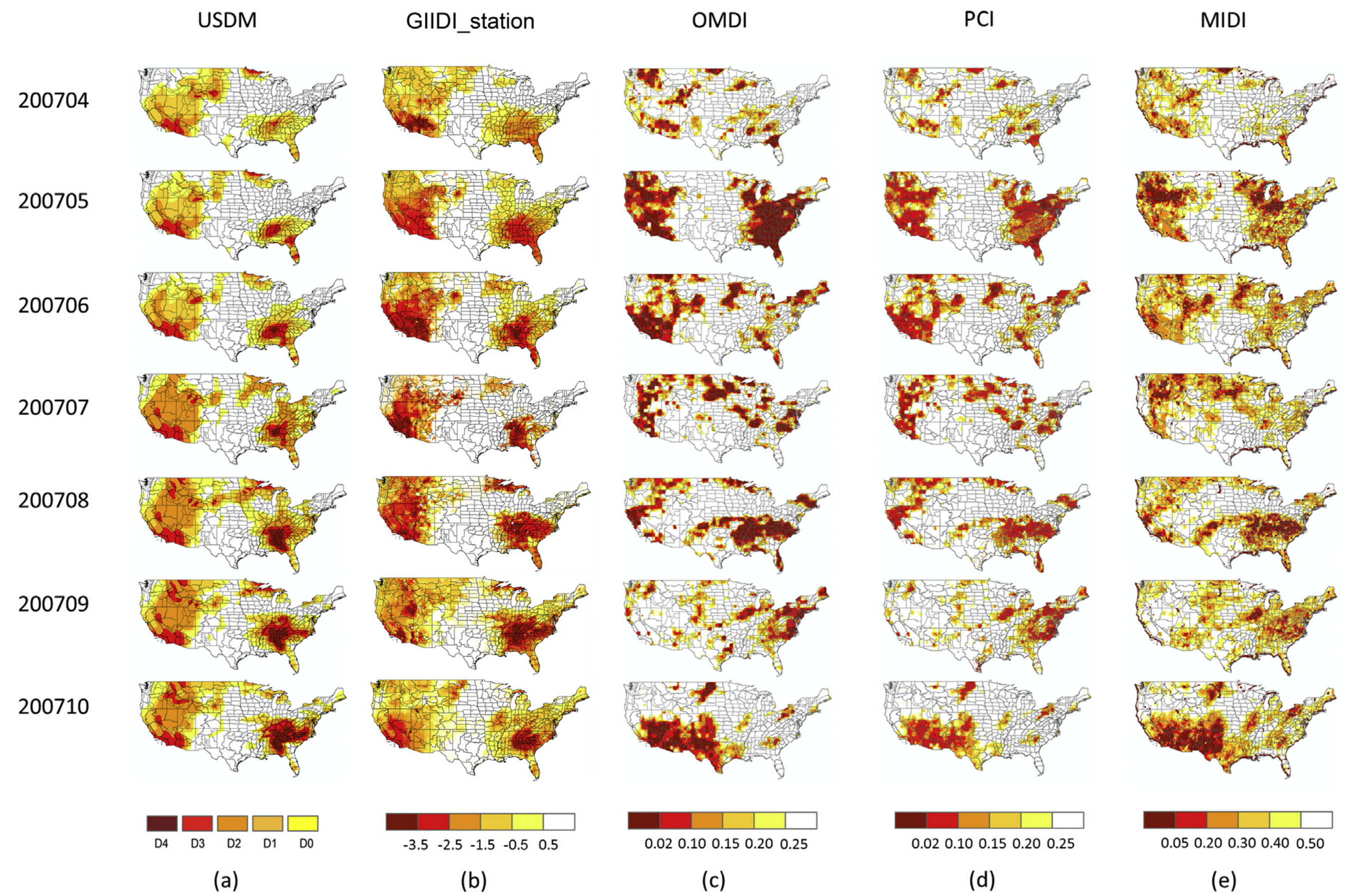

Fig. 7. Drought conditions in the US monitored by multiple drought indices from April to October in 2007. The first column displays the observed USDM drought data for the period of April to October, while the second to fifth columns show the GIIDI_station, OMDI, PCI and MIDI, respectively. For USDM, D0-D4 represents the different severities of drought conditions; for columns 2–5, lower values stand for more severe drought.

variables. For example, Hao et al. (2015) used the *in-situ* based SPEI as the dependent variable to composite TCI, PCI and SMCI for establishing OMDI. Brown et al. (2008) only used PDSI as the dependent variable to combine the multi-variable when calculating VegDRI. Such approach reflects a limited perspective on drought, as there are differences between the station-based drought indices. We used three different *in-situ* based drought indices (PDSI, Z-index and SPI) as the dependent variables to composite the integrated drought indices. The evaluation of PCA output in our results indicates that GIIDI_station could synthetically contain the most information from dependent of variable from PDSI, Z-index and SPI. The integration of the information from PDSI, Z-index and SPI makes GIIDI_station shows better consistency with USDM in different severity of drought conditions since USDM itself contains the combined information from different drought indices such as PDSI, Z-index and SPI.

Third, the selection of single indices is another factor that potentially contributes to the good performance of GIIDI_station. Previous studies indicate that the time series analysis based single drought indices (PCI, TCI, VCI and SMCI) performed better than other types of single drought indices such as Perpendicular Drought Index (PDI), Modified Perpendicular Drought Index (MPDI) and Temperature Vegetation Dryness Index (TVDI) (Zhang et al., 2017). PCI is derived from the scaled precipitation information based on TRMM data, TCI is derived from land surface temperature information, VCI is about the condition of vegetation growth, and the SMCI is soil moisture condition from AMSR-E data. These indices are not fully correlated with each other. In this regard, PCI, SMCI, VCI and TCI were selected to composite GIIDI_station.

Table 3
Comparison of the performance of GIIDI_station with six commonly used remote sensing drought indices using 8 *in-situ* drought indices. r is the correlation coefficient between two variables. *denotes the maximum value in each column. GIIDI_station, MIDI, OMDI, PCI, TCI, VCI and SMCI are seven remotely sensed drought indices; PDSI, Z-Index, 1-, 2-, 3-, 6-, 9-, 12-, and 24-month SPI are *in-situ* drought indices.

Drought indices	r (n = 24080)							
	PDSI	Z	SPI-1	SPI-3	SPI-6	SPI-9	SPI-12	SPI-24
GIIDI_station	0.801*	0.877*	0.892*	0.803*	0.795*	0.671*	0.632*	0.493*
OMDI	0.496	0.825	0.871	0.686	0.592	0.449	0.395	0.354
MIDI	0.504	0.788	0.807	0.662	0.580	0.445	0.399	0.345
VCI	0.622	0.313	0.234	0.564	0.582	0.584	0.548	0.390
PCI	0.440	0.806	0.865	0.559	0.398	0.350	0.303	0.211
TCI	0.542	0.589	0.487	0.515	0.471	0.423	0.379	0.278
SMCI	0.370	0.451	0.426	0.389	0.331	0.297	0.259	0.197

Table 4
Comparisons of the RMSE between GIIDI_station and other commonly used remote sensing based drought indices. *denotes the minimum value in each column. GIIDI_station, MIDI, OMDI, PCI, TCI, VCI and SMCI are seven remotely sensed drought indices; PDSI, Z-Index, 1-, 2-, 3-, 6-, 9-, 12-, and 24-month SPI are *in-situ* drought indices.

Drought indices	RMSE (n = 24080)							
	PDSI	Z	SPI-1	SPI-3	SPI-6	SPI-9	SPI-12	SPI-24
GIIDI_station	0.858*	0.783*	0.709*	0.849*	0.861*	0.956*	0.998*	1.223*
OMDI	3.011	0.803	0.732	1.305	1.805	2.303	2.499	2.667
MIDI	2.985	0.823	0.776	1.344	1.878	2.397	2.589	2.697
VCI	2.658	2.244	1.159	1.075	1.082	1.058	2.068	3.074
PCI	3.440	0.865	0.801	2.559	2.598	2.650	2.703	2.811
TCI	2.709	2.289	1.166	1.145	1.271	1.223	1.379	1.278
SMCI	2.856	2.234	1.183	1.324	1.245	1.255	1.265	1.278

To summarize, GIIDI_station can be more confidently applied across different environmental regions when compared to the existing remotely-sensed drought indices and it has potential to be used as a mixture of meteorological drought and agricultural drought index. However, the application of GIIDI_station is limited to regions with available meteorological ground observations. Establishing reliable integrated remote sensing based drought indices which could be applied in various environmental regions without relying on ground observations is an important avenue for future work (e.g., Jiao et al., 2019).

6. Conclusions

Reliable drought monitoring is fundamental to planning and mitigation of drought impacts. Given the complexity of drought, a drought index from single data source, which typically represents a limited perspective on drought impacts, may not be sufficient for comprehensive drought detection. This study outlines a multi-index drought monitoring framework (GIIDI_station). GWR model and PCA were used to integrate multi-sensor remote sensing data and *in situ* based drought indices in this framework. The GIIDI_station, along with the USDM, PCI, OMDI and MIDI, were assessed for their ability to characterize moderate, severe and extreme drought examples in the United States. Their performance was also compared to information provided by *in-situ* drought indices (PDSI, Z-index, SPI-1, SPI-3, SPI-6, SPI-9, SPI-12, and SPI-24), and the relationship between GIIDI_station and a range of environmental factors was also investigated.

Based on the case studies, the GIIDI_station generally captures the drought severity as indicated by USDM. The results also indicated that

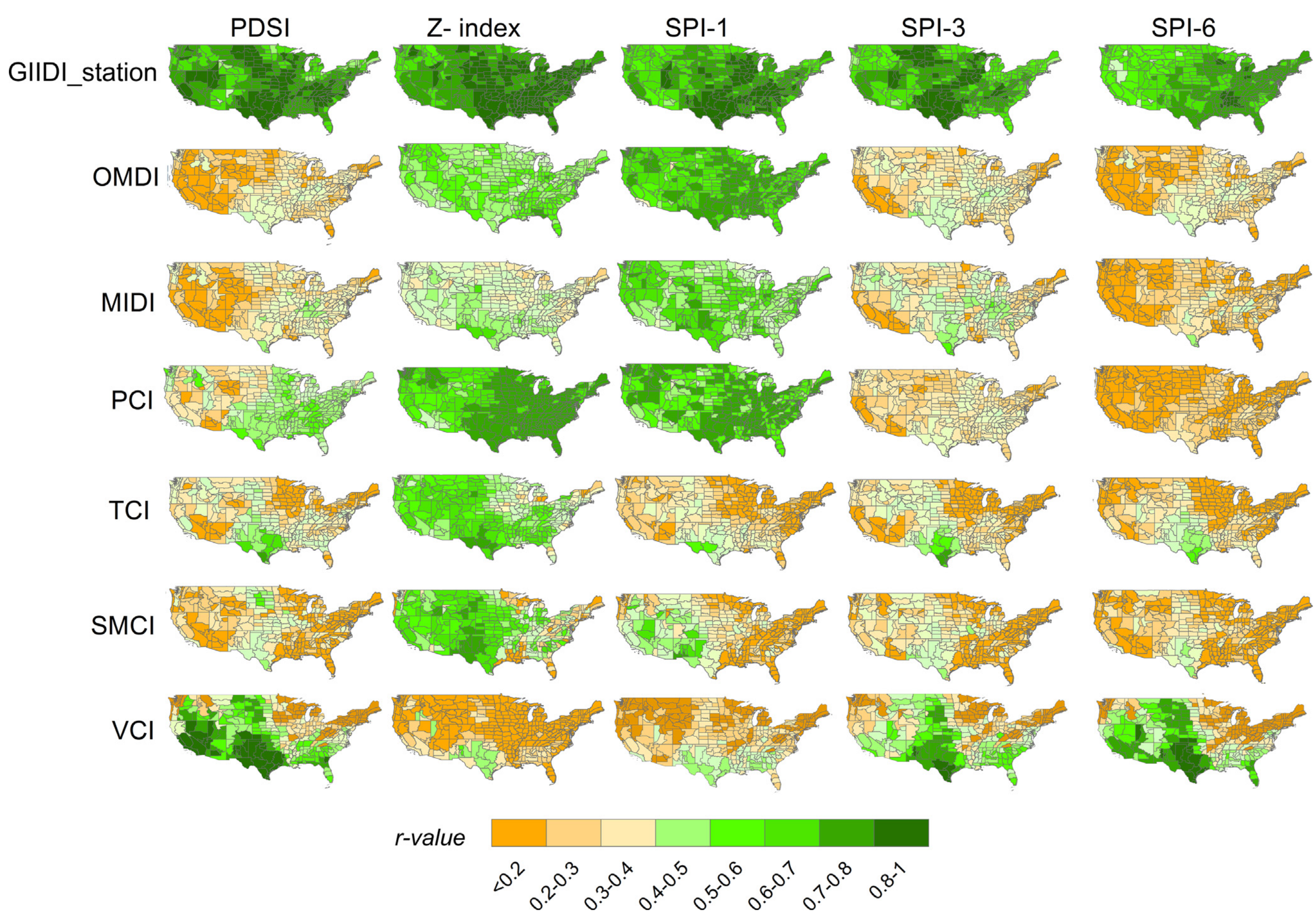

Fig. 8. Spatial distribution across climate divisions of the correlations (r-value) between remote-sensing-based and *in-situ*-based drought indices for the entire growing season (April–October) of 2002–2011.

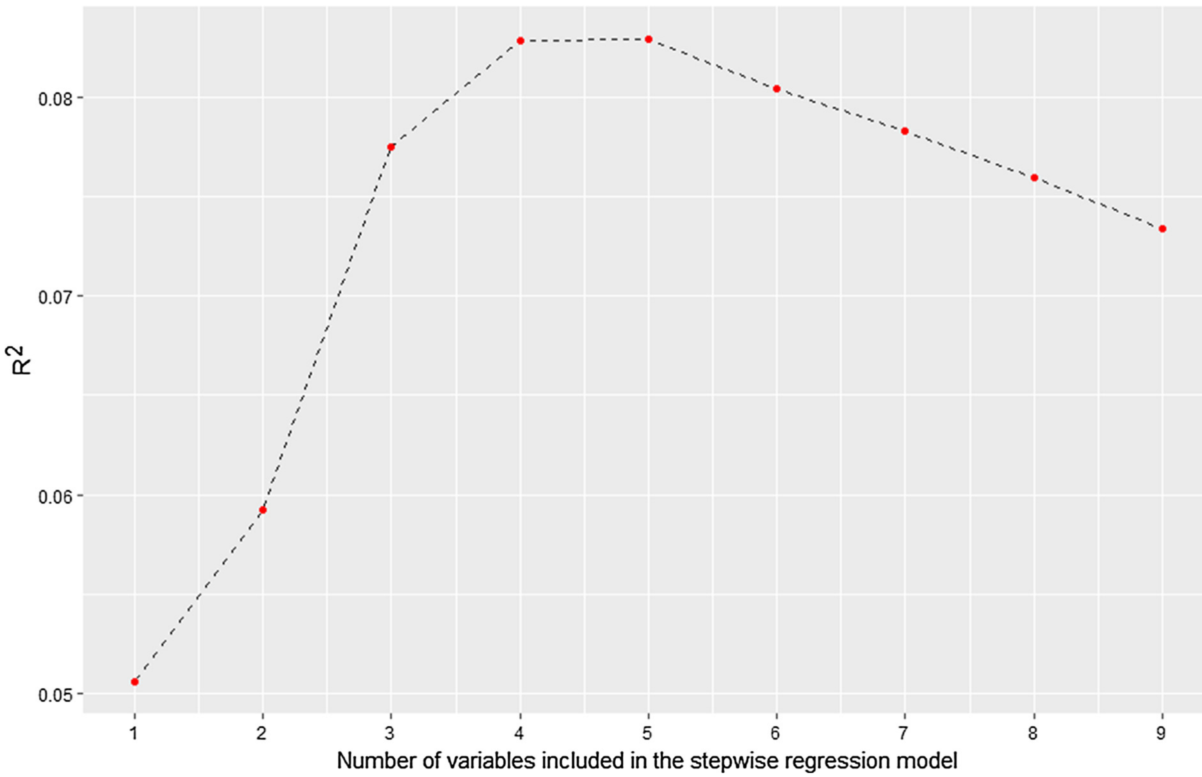

Fig. 9. Results of regression model showing the number of variables included in the regression model and the performance of GIIDI_station. Values on the y-axis are the adjusted R^2, x-axis stands for the number of variables included in the stepwise regression model.

the GIIDI_station had the strongest correlation with *in-situ* drought indices when compared to the other remote sensing based indices in most climate divisions, and its applicability is not significantly affected by environmental factors such as precipitation, temperature, soil available water holding capacity, soil moisture, soil permeability, soil drainage class, hydrological group, organic material in soil and LULC. We emphasize that GIIDI_station is not meant to replace any other drought indices but as an additional source of information and a new framework, which combines different perspectives afforded by remote sensing and *in-situ* data, and has great potential for monitoring drought conditions across diverse climate conditions.

Declaration of interest

None.

Acknowledgments

We acknowledge support from Division of Earth Sciences of National Science Foundation (NSF EAR-1554894) and from the Agriculture and Food Research Initiative program (2017-67013-26191) of the USDA National Institute of Food and Agriculture. We would like to thank the editor and two anonymous reviewers for their constructive comments and suggestions, which we believe significantly strengthened our manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2019.04.037.

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